



FINAL REPORT

Towards Quality-Aware Big Data Integration for Crowdsourced Road Sensing System

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16. Abstract With nearly a billion automobiles on the road today, the current transportation systems have begun to show signs of serious strain, such as congestion, traffic accident, excessive energy consumption and increased emission level. To mitigate these problems, in this project, we propose a Quality of Information (QoI) aware crowdsourced road sensing system that can monitor a wide spectrum of road events, such as congestions, accidents, potholes, bumps, and road signs. Our crowdsourced road sensing system gathers information from a variety of sources, including not only connected vehicular smartphones, but also social media as well as internet users, and thus is able to build up a complete and accurate view of road and traffic conditions. To integrate the information from multiple sources that observe the same road events, we develop a novel QoI aware information integration framework that can automatically estimate the QoI of each source and incorporate the estimated QoI into the information integration process. The proposed system will significantly improve the coverage and quality of assisted driving and road navigation services, providing drivers with more timely and accurate advisory and warning messages and thus improving their driving safety, efficiency, and comfort.			
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I. Introduction

With nearly a billion automobiles on the road today, and a doubling projected over the next decade, motor vehicles are critical to addressing society's basic mobility needs. However, the increasing travel demand and resulting vehicle roadway traffic have created challenges for transportation system planners and operators to reduce congestion, increase safety, and maintain and improve the environment. To address these issues more accurate and timely data on roadway conditions and status, and travel and driving behavior are needed.

Traditionally, transportation system planners and operators have relied primarily upon roadway sensors, driver supplied surveys, census information, and roadway-related event reports (e.g., Police Accident Reports) to provide data for their use. Unfortunately, the prohibitively high deployment cost of such devices makes it impossible to achieve largescale deployment, leading to limited road coverage and delayed information update.

Technology is rapidly evolving and we have now entered an era of 'Big Data' in which new sources of data from pervasive mobile devices, such as vehicle- and vehicle occupant-based sensors, are becoming available. These crowdsourced mobile data potentially provide a great resource to address transportation system issues. Towards this end, in this project, we propose a crowdsourced road sensing system. As shown in the figure, Our crowdsourced road sensing system gathers information from a variety of sources, including individual vehicles with occupant-carried mobile devices (e.g., smartphones) containing a variety of on-board sensors (e.g., GPS, accelerometer, gyroscope, compass, camera, etc.), as well as internet based social media users, and thus is able to build up a complete and accurate view of transportation system performance, traffic-related events, travel behavior, and roadway conditions.

To illustrate the effectiveness of the proposed road sensing system, in our recent work published in the 85th IEEE Vehicular Technology Conference (VTC 2017), we describe the design, implementation and evaluation of VehSense, a smartphone based slippery road detection system.

Slippery road conditions during winter time, i.e., snowy, slushy, or icy pavement, are major concerns for road safety. In the U.S., winter road maintenance accounts for roughly 20% of state Department of Transportation maintenance budgets. Despite this investment, 24% of weather-related vehicle crashes occur on snowy, slushy or ice pavement, over 1,300 people are killed and more than 116,800 people are injured annually¹. Keeping roadways in good condition is challenging because inclement weather degrades road condition just over a short period of time. Because government agencies only have limited resource, prioritizing which roads need snowplowing or deicing comes of interest. More importantly, we need to inform drivers about hazardous road conditions, especially when lighting is poor during snowfall or sleet.

To address this need, we describe the design, implementation and evaluation of VehSense, a smartphone based vehicular sensing system. Our focus in this paper is on the slippery road detection component of VehSense, we defer a discussion of our on-going project on VehSense, a comprehensive crowdsourcing platform, to future work. Particularly, VehSense uses inertial sensors (i.e., accelerometers and gyroscopes), GPS in a smartphone and reads from vehicle's Controller Area Network (CAN) bus (with smartphone connects with an OBD-II adaptor via Bluetooth). The system relies on the mobility of vehicles to traverse roads being monitored. A smartphone based approach is a good match for road monitoring problem because: 1) it can be easily integrated with a navigation application to provide slippery road information along with other rich sensing data; 2) it is cost-effective, since sensing leverages existing sensors and communication infrastructure. Although our method requires a OBD adapter to interface with vehicle's CAN bus, the adapter only costs about \$20 dollars; and 3) it provides a reliable and systematic approach, since data are aggregated from multiple vehicles.



¹ U.S. Federal Highway Administration http://www.ops.fhwa.dot.gov/weather/weather_events/snow_ice.htm

Only relying on the OBD-II interface to detect vehicle skidding is possible but problematic. Relevant vehicle sensor data (e.g., suspension deflection, antilock braking system and traction control) are considered proprietary by vehicle manufactures and are not available. In addition, the CAN message protocol can differ significantly by model, year and make of the vehicle, resulting in extra setting and calibration cost for different vehicles.

The intuition behind the proposed slippery road detection algorithm is simple. The smartphone fixed inside a vehicle collects 3-axis acceleration and gyroscope data at a high frequency. Meanwhile, it gathers vehicle speed data from vehicle's CAN bus via OBD. Each of these sensory data provides a way to get vehicle speed: 1) the acceleration data can be used to estimate the vehicle speed relative to the ground, which we refer to it as the ground speed; 2) the vehicle speed data reported by the wheel speed sensors (a type of tachometer from the CAN network), which we refer to it as the wheel speed. The key observation here is that wheel speed sensors measure the rotation speed of the wheel, however, the "actual" speed of the vehicle might be different: During normal driving conditions, there will be a good match between the ground speed and the wheel speed, but if the road is slippery, the instantaneous ground speed and wheel speed maybe different, which indicates skidding events.

This simple description hides various design challenges of the proposed VehSense for slippery road detection, we will elaborate our solutions in the following sections. The contributions of this work are:

1. To the best of our knowledge, VehSense is the first smartphone based system for detecting slippery road conditions. It utilizes low-cost, off-the-shelf OBD-II adaptor. It is easy to install and does not require user calibrations. The source code of the sensing component in VehSense is available online². It is capable of collecting OBD-II data at about 15 Hz (via Bluetooth with ELM 327³ integrated circuit).
2. We developed a skidding detection algorithm that is able to successfully detect slippery locations. Our field test at Buffalo, New York has a very low false-positive rate for skidding, flagging less than 3% of events from skidding as normal on our field test.

II. System Design

A. Overview

The VehSense system consists of equipped vehicles and a central server, as illustrated in Fig. 1. Each vehicle collects the following raw information: <time, location, acceleration, rotation, wheel speed, RPM>. The first four parameters come from the sensors in a smartphone: GPS provides time and location data at a rate of 1 Hz. 3-axis accelerometer and gyroscope provides acceleration and rotation data at a rate of 200 Hz. In the proposed slippery detection algorithm, acceleration and rotation data are combined to estimate the ground speed (i.e., the speed of a vehicle relative to the ground).

Although GPS also provides speed information, our field test shows that GPS on the smartphone does not have the necessary precision for the slippery road detection. The last two parameters come from the OBD-II interface, wheel speed and RPM (Revolutions per Minutes, which measures the engine speed) data are collected at 10 Hz.

These sensing data streams are processed by the smartphone to produce vehicle skidding detections. The vehicles transmit collected sensor data back to the backend server through various channels, e.g., WiFi or cellular network. In our preliminary work, a vehicle-to-vehicle sharing mechanism is also implemented to let two nearby vehicles sharing their data, thus increasing the possibility that the data reaches the backend server [1]. The central server clusters skidding events reported by multiple vehicles, and applies data aggregation and fusion techniques (e.g., truth discovery), resulting in the output of the central server: a series of slippery road segments warnings with varying degree of possibility and severity. Finally, the slippery road warning information can be integrated into a navigation application, thus raising the awareness of potential slippery hazards and help to reduce the risk of crashing.

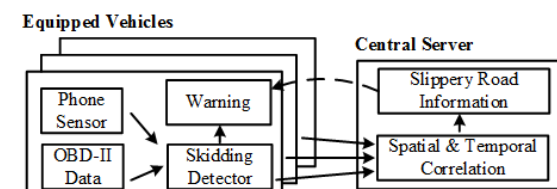


Figure 1. System overview

² VehSense on Github, <https://github.com/yunfeihou/VehSense>

³ ELM327, Elm Electronics <https://www.elmelectronics.com/ic/elm327/>

B. Vehicle Testbed

The hardware for equipped vehicles is a smartphone, an OBD-II adapter and preferably a car charger (as shown in Fig. 2). Latest version of the VehSense app runs on Android 6.0 Marshmallow and supports OBD-II adapters with ELM 327 integrated circuit (The ELM 327 chip from Elm Electronics is one of the most popular OBD-II-to-PC interpreter, and supports the standard OBD-II protocols). The smartphone can be placed at any convenient locations for the driver, as long as it is firmly attached to the vehicle.



Figure 2. Equipped vehicle

III. Skidding Detection Algorithm

The idea behind the skidding detection algorithm is that the wheel speed (i.e., the vehicle velocity inferred by sensing the rotations of the wheel) will be significantly different from the ground speed (i.e., the actual velocity of a vehicle) caused by vehicle skidding. With VenSense, the wheel speed can be collected from OBD-II readings, at the same time, vehicle's ground speed can be inferred from smartphone sensor readings. Thus we can detect skidding conditions by analyzing the deviation of the differences between those two readings (i.e., a high deviation of their difference indicates slippery road surface). More specifically, the proposed algorithm works as follows:

Step 1) Preprocessing and Calibration of the Acceleration Vector

In general, the smartphone may be in an arbitrary orientation with respect to the vehicles. Additionally, the calibration process needs to account for the gravitational acceleration. This orientation problem has been extensively studied, please refer to [2] for details. The proposed skidding detection algorithm uses the acceleration vector (based on both vehicle's acceleration and rotation) towards the vehicle's moving direction, denoted by $a(t)$ at time t . The raw data are passed through a low-pass filter (e.g., 2nd order Butterworth filter) to remove their noise component.

Step 2) Ground Speed Estimation

The instantaneous ground speed $v_{ground}(t_i)$ at time t_i is calculated by integrating $a(t)$ within a slicing time window (will be explained in Step 3)) plus the wheel speed $v_{wheel}(t_0)$ at the beginning of that time window t_0 . It is defined as:

$$v_{ground}(t_i) = v_{wheel}(t_0) + \int_{t_0}^{t_i} a(t) dt$$

More specifically, $v_{wheel}(t_0)$ serves as the “base” speed for the estimation, and the trapezoidal integration is used to calculate the speed change due to vehicle acceleration/deceleration.

Step 3) Skidding Detection

The time series of $v_{ground}(t_i)$ and $v_{wheel}(t_i)$ data are evaluated by a slicing time window. Let $T(t_0)$ denotes the slicing window with a length of len seconds, and t_0 indicates the beginning of the current time window being examined. The algorithm calculates the standard deviation of the set of absolute difference between the ground speeds and the wheels speeds in $T(t_0)$, which is defined as follows:

$$\sigma = std(\{abs(v_{ground}(t_i) - v_{wheel}(t_i)) \mid t_i \in T(t_0)\})$$

where σ is the standard deviation, std and abs are functions to calculate standard deviation and absolute value respectively.

If $\sigma > d_{skid}$, where d_{skid} is a pre-defined threshold for vehicle skidding, the algorithm asserts a skidding event is detected.

Step 4) Advancing the Slicing Time Window

The slicing time window is advanced by len seconds if the vehicle is accelerating or decelerating. If the vehicle is moving in a constant speed or stopped, a smaller advancing step (1 second in our experiment) is applied in order to capture the changes of vehicle movements.

IV. Evaluation

The goal of this evaluation is to demonstrate that VenSense is able to detect skidding events and monitor slippery road conditions effectively. A 2009 Honda Civic was equipped with a LG Nexus 5 smartphone and a Bluetooth OBD-II adaptor. The proof-of-concept test consists of four trials of driving: one trail was conducted during normal driving condition, and three trails after about 6 inches of snow on unplowed road (Fig. 3). Each trial was conducted on a different day that spans in January 2016, at Buffalo, NY. Due to the safety concerns, we tested our system in a parking lot and limited the vehicle speed to 20 mile per hour (about 9 meter per second). During the trails, the driver accelerates to 20 mph and then brings the vehicle to a full stop. The driver was asked to drive the car as in the normal conditions. During a stop-and-go process, if the overall handling of the vehicle has been affected, the driver will manually record the number of skidding events and its severity. We focused on vehicle skidding during acceleration and deceleration without directional or yaw changes.

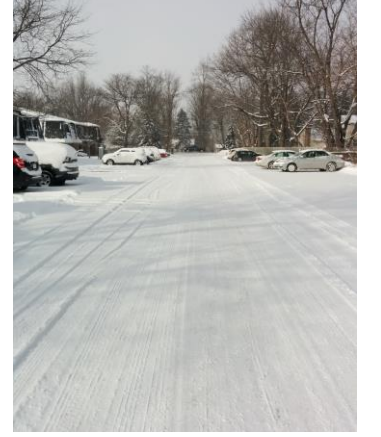


Figure 3. Testing Environment

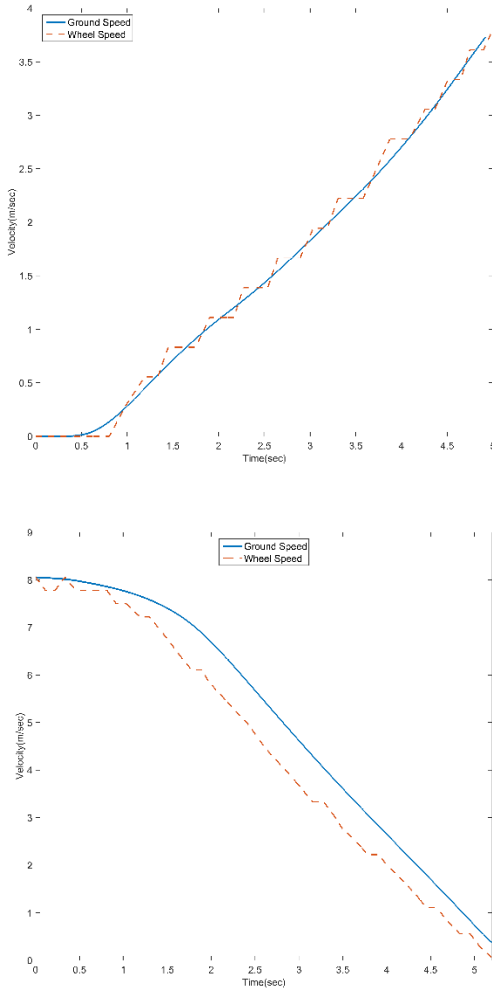


Figure. 4

Fig. 4 shows the ground speed and wheel speed during normal driving conditions. As we expected, there is a good match between ground speed and wheel speed during both vehicle acceleration and deceleration. The “staircase-shape” of the wheel speed is caused by the data type specified in the OBD-II standard: wheel speed is reported as an integer value.

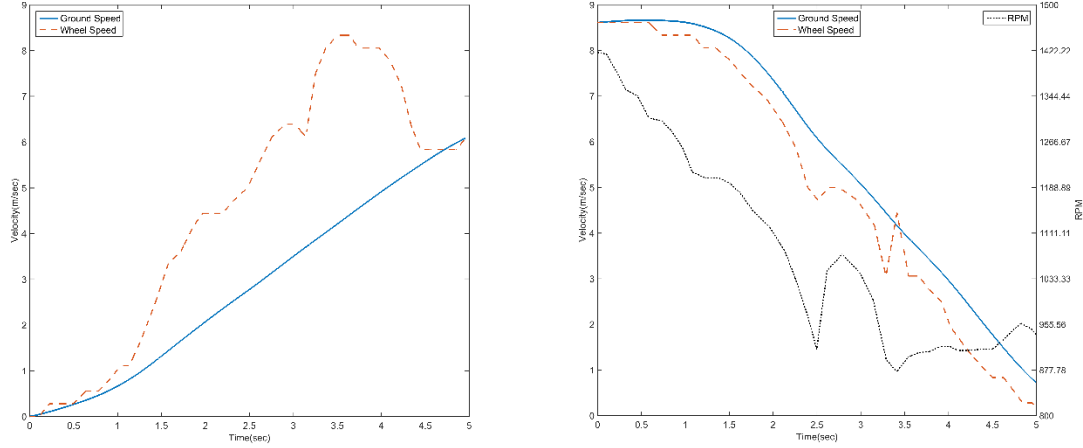


Figure 5.

Fig 5 compares the ground speed and the wheel speed during typical skidding events. When vehicle is skidding, at around 1.5 sec. to 4 sec. in Fig. 5 a), there is a significant different between ground speed and wheel speed, after the skidding event, wheel speed is in line with the ground speed. It shows that the proposed skidding detection algorithm is an effective approach. Skidding detection during deceleration is more challenging, as shown in Fig. 5 b), the variation between wheel speed and ground speed is notable but much less significant. This is caused by the electronic stability control and anti-lock brake systems in modern vehicles. One possible idea to improve the detector is to utilize vehicle RPM data, since such systems will result in gear shifts and engine outputs changes. We will explore this idea in future works.

The false negative and false positive rates are 5% and 10% respectively in our experiment, with $d_{skid} = 0.8$ and $len = 5$ sec. There are a total of 30 stop-and-go processes during the snow trails, and 19 skidding events are recorded. The slicing window length len and skidding threshold d_{skid} are determined as follows: In order to cover the entire skidding event, len is set to twice of the skidding duration (typical skidding lasted for about 2.5 seconds in our test). It is worth noting that as long as the slicing window covers most of a skidding event, VehSens is able to detect skidding events. This is because we are using the variations as the indicator, the exact speed difference will not affect too much of the result. The d_{skid} is determined based on the variation retrieved from normal driving conditions, we used twice of the normal value as the skidding threshold.

This empirical method on choosing default parameters makes VehSens easy to deploy: after installation, VenSens will atomically determines the d_{skid} by monitoring normal driving conditions, no action is required from the users. Different value of parameters has also been tested, as shown in Table I, the parameters determined by the empirical method provides good detection accuracy (although not always getting the minimum false negative and false positive rates).

Table I False Negative/ False Positive Rates with Different Parameters

	$d_{skid} = 0.6$	$d_{skid} = 0.7$	$d_{skid} = 0.8$	$d_{skid} = 0.9$	$d_{skid} = 1$
$len = 3$	6%/7%	6%/4%	6%/2%	10%/1%	21%/0%
$len = 4$	6%/5%	11%/4%	10%/2%	10%/2%	26%/0%
$len = 5$	0%/6%	6%/4%	10%/2%	10%/2%	26%/0%
$len = 6$	0%/11%	11%/7%	10%/5%	10%/5%	26%/0%
$len = 7$	0%/15%	6%/11%	6%/8%	6%/5%	26%/0%

V. Related Work

An effective slippery road detection system is beneficial for traffic safety and road maintenance. Several vehicular sensing systems have been proposed for detecting slippery roads. These systems can be categorized into: a) image-based techniques [3]–[6], which require stereo cameras and/or infrared sensors for recording and are

computationally intensive to process, b) proprietary OBD-II based techniques [7], [8], which require proprietary data from the vehicle's antilock braking system (ABS) or ABS equivalent systems (e.g., individual wheel speed, steering angle). Vehicle manufactures generally do not allow proprietary data to be accessed by the OBD-II connection, and different manufacturers are using different CAN message sets. To the best of our knowledge, VehSense is the first system that attempts to detect slippery road condition using smartphones and is compatible with most, if not all, vehicle manufactures.

The most related project to the proposed systems is DataProb [8], which is based on the same hardware settings as those of VehSense. No conclusions were drawn from the DataProb project, due to limited amount of data. The DataProb project also explored the mismatch between wheel speed and ground speed as a detector for skidding, however, GPS speed readings was used as the ground speed which does not provide enough sample rate (GPS sample rate is up to 1 Hz) and accuracy.

VI. Conclusion and Future Work

In this paper, we present the design, implementation, and evaluation of VehSense, a vehicular sensing platform that uses smartphones and OBD-II adaptors for slippery road detection. The system utilizes standardized OBD-II commands and Android sensor readings, which makes it compatible with most of the passenger vehicle. It does not require user calibration and can be readily integrated into navigation applications. Our pilot study at Buffalo, NY, shows that the system is an effective skidding detector in snow days.

In the future, we want to add more capabilities such as integrating information from heterogeneous sources and supporting environmental sensors. More rigorous and larger scale experiments are also necessary. The objective of the VehSense system are: 1) develop a low-cost crowdsourcing data collection system; 2) explore how to integrate this data with other contextual information and use it to detect slippery road, pavement roughness and other potential uses; and 3) evaluate how to inform driver about safety information without creating distractions.

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